ANN Methods in photovoltaic system

- MPPT controller (uniform & non-uniform irradiance conditions)
- Performance of TFFN, RBF and ANFIS networks for different technology of PV modules
Other Advantages of PV System:
* Unlimited fuel supply
* Clean - no pollution or emissions & water
* Silent
* Minimal visual impact
* Low maintenance
* Easily expanded
* Generates at load (Distributed Generation)

Applications:
* Power supplies for satellite communications
* Large power stations feeding electricity into the grid

Source: Global Energy Network Institute (GENI)
MPPT controller for uniform condition

Challenges to the widespread use of photovoltaic system:

✓ high cost of module materials and encapsulation
✓ PV power conditioning system (critical issue for efficient PV system)
✓ intermittency output characteristics
✓ non-linear characteristic

Lower Efficiency

PV system should be operated optimally

Maximum Power Point Tracking (MPPT) Control system

The state of the art techniques to track the maximum available output power of PV systems
MPPT controller for uniform condition

MPPT controller works based on certain developed algorithms:
- Perturbation and observation (P&O)
- Incremental conductance
- Fractional open circuit voltage methods

P&O and incremental conductance methods:
- Widely used in PV applications
- Combine to improve the tracking accuracy
- The efficiency of tracking techniques strongly depends on iteration step size

Fractional open circuit voltage method:
The optimal point → a constant value $k = \text{MPP Voltage/}V_{oc}$

Conventional methods weaknesses!!!
The Weaknesses of Conventional MPPT Controllers

P&O and incremental conductance methods:
- Continue oscillation → causes power losses
- Algorithms # to the fast dynamic response
- Very difficult to get an analytical expression in different solar cells technologies

Fractional open circuit voltage method:
- MPP voltage -Vs- irradiance might not be same for different solar cell technologies
- Therefore, it is impossible to determine the optimum voltage by using only one linear function of the open circuit voltage
ANN-FUZZY LOGIC SCHEMES BASED MPPT CONTROLLER

Mathematical Model from Sandia National Laboratory

I-V and P-V characteristics of PV modules ($E=100-1000\,\text{W/m}^2$, $T_c=50^\circ\text{C}$)

**PV Modules Technology**

**Siemens SM-55 PV (c-Si)**
- High efficiency output power under reduced light condition by using pyramidal textured surface

**First Solar FS-50**
- Thin film CdTe
- Thin layers of compound semiconductor material with low temperature coefficients which provides for cost effective and greater energy production

**USSC US-21 (3j a-Si)**
- Composed of encapsulated polymer inside a rigid anodized aluminum frame
ANN-FUZZY LOGIC CONTROL SCHEMES BASED MPPT CONTROLLER

Motivation-1

Intelligent System (ANN)

✓ modeling
✓ identification
✓ optimization
✓ forecasting
✓ control

Solve the engineering problems:
• symbolic reasoning
• flexibility
• explanation capabilities
• capable to handle and learn the non-linear, large, complex and even incomplete data patterns

Complex System (different fields of application)

Compared standard linear model for optimization methods:
✓ compact solution for multi-variable problems
✓ not require the knowledge of internal system parameters
✓ only training process is required and the output parameters are directly determined without solving any non-linear mathematical equations or statistical assumptions as in the conventional optimization methods
The important steps of ANN method:
- Selection of training data set
- Training process
- Validation

Selection of training data set:
- To set the functions between input and output through the hidden layers (training data set should be selected to cover the entire region where the network is expected to operate)
- Training data pattern \[ [V_{mp}, P_{mp}] = f(E, T_c) \]; following the mathematical model
- Total data (228 sets) for operating conditions between 15-65°C and 100-1000W/m²
ANN-FUZZY LOGIC CONTROL SCHEMES BASED MPPT CONTROLLER

TFNN:

In the hidden and output layers, the sigmoid function is utilized for the input-output characteristics of the nodes. For each node $i$, the output $O_i(k)$

$$O_i(k) = \frac{1}{1 + e^{-I_i(k)}}$$

$I_i(k)$: the input signal to node $i$ at the $k$-th sampling and this is given by the weighted sum of the input nodes

$$I_i(k) = \sum_j w_{ij}(k)O_j(k)$$

$w_{ij}$: the connection weight from node $j$ to node $i$

$O_j(k)$: the output from node $j$

During the training, the connection weights $w_{ij}$ are tuned recursively until the best fit is achieved for the input–output patterns based on the minimum value of the sum of the squared errors (SSE)

$$SSE = \sum_{k=1}^N (t(k) - O(k))^2$$

$N$ is the total number of training patterns, $t(k)$ and $O(k)$ are the $k$-th output target and estimated values of MPPs voltage-power

During the training process:
learning rate = 0.2
momentum rate = 0.85
ANN-FUZZY LOGIC CONTROL SCHEMES BASED MPPT CONTROLLER

ANN Training Results

Number of hidden nodes based on the minimum of sum of the squared error (SSE)

The cells made of crystalline silicon generally have higher fill factor than those of the others
“more hidden nodes are required to accurately represent the characteristics of crystalline silicon cells”
ANN-FUZZY LOGIC CONTROL SCHEMES BASED MPPT CONTROLLER

Verification of ANN training results → during 12 hours of simulation time

\[ J_V = \int (V_{dc} - V_{mp})^2 \, dt \]

\[ J_P = \int (P_{dc} - P_{mp})^2 \, dt \]

\( V_{mp} \) & \( P_{mp} \): MPP points from P-V curve (target in training process)

\( V_{dc}^* \) and \( P_{dc}^* \): optimum voltage and power from ANN

Smallest values of both \( J_V \) and \( J_P \) are expected in this case that indicates how close the values between the optimum and the target.

<table>
<thead>
<tr>
<th>PV Modules</th>
<th>Performance Index</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( J_V )</td>
</tr>
<tr>
<td>SM-55</td>
<td>0.1674</td>
</tr>
<tr>
<td>FS-50</td>
<td>0.6774</td>
</tr>
<tr>
<td>US-21</td>
<td>0.2071</td>
</tr>
</tbody>
</table>

“the prediction of global MPP voltage as a reference signal for controller is one of the solutions to improve the stability of the MPPT controller”
ANN-FUZZY LOGIC CONTROL SCHEMES BASED MPPT CONTROLLER

Polar Coordinated Fuzzy Controller

Advantages:
* no required accurate description of the system to be controlled
* no wide parameter variations with respect to the standard regulators

Fuzzy logic Controller

- MPP voltage as reference
- To establish the control signal in real-time for keeping the voltage of PV systems at optimum operating point
- Applied for the first time in the MPPT system

Similar fuzzy logic rules in the PSS application
ANN-FUZZY LOGIC CONTROL SCHEMES BASED MPPT CONTROLLER

Three important stages as Rule base, Fuzzification and Defuzzification

Rule base:
(Fuzzy rules assignment table)

<table>
<thead>
<tr>
<th>e</th>
<th>NB</th>
<th>NM</th>
<th>NS</th>
<th>Z</th>
<th>PS</th>
<th>PM</th>
<th>PB</th>
</tr>
</thead>
<tbody>
<tr>
<td>NB</td>
<td>Z</td>
<td>NS</td>
<td>NS</td>
<td>Z</td>
<td>PS</td>
<td>PM</td>
<td>PB</td>
</tr>
<tr>
<td>NM</td>
<td>PS</td>
<td>Z</td>
<td>NS</td>
<td>NS</td>
<td>NM</td>
<td>NM</td>
<td>NB</td>
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<tr>
<td>NS</td>
<td>PS</td>
<td>PS</td>
<td>Z</td>
<td>NS</td>
<td>NS</td>
<td>NM</td>
<td>NM</td>
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<tr>
<td>Z</td>
<td>PM</td>
<td>PS</td>
<td>PS</td>
<td>Z</td>
<td>NS</td>
<td>NS</td>
<td>NM</td>
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<tr>
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<td>PM</td>
<td>PM</td>
<td>PS</td>
<td>PS</td>
<td>Z</td>
<td>NS</td>
<td>NS</td>
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<tr>
<td>PM</td>
<td>PB</td>
<td>PM</td>
<td>PM</td>
<td>PS</td>
<td>PS</td>
<td>Z</td>
<td>NS</td>
</tr>
<tr>
<td>PB</td>
<td>PB</td>
<td>PB</td>
<td>PB</td>
<td>PB</td>
<td>PB</td>
<td>PB</td>
<td>PB</td>
</tr>
</tbody>
</table>

\[ e(k) = V_{dc}^*(k) - V_{dc}(k) \]

\[ \text{Int}_e(k) = \text{speed deviation} \]

\[ e(k) = \text{acceleration} \]

Phase plane of fuzzy logic control with polar information

\[ Z(k) = \left[ \text{Int}_e(k), A_s e(k) \right] \]
**Fuzzification stage:** numerical variables are transformed into linguistic variables

**Numerical variables:** angle & radius

**Linguistic variables:**
- **angle:** increase and reduction in the operating voltage;
- **radius:** near and far from target point

θ(k) = tan⁻¹ \( \left( \frac{A_s e(k)}{\text{Int}_e(k)} \right) \)

\[
D(k) = \sqrt{(\text{Int}_e(k))^2 + (A_s e(k))^2}
\]

\[
G(D(k)) = \begin{cases} 
  \frac{D(k)}{D_r} & \text{for } D(k) \leq D_r \\
  1.0 & \text{for } D(k) \geq D_r 
\end{cases}
\]

Tuning parameters of \( A_s \) and \( D_r \) are specified at 5.0 and 0.35, respectively

**Defuzzification stage:** linguistic variables are converted back into numerical variables *(weighted averaging defuzzification algorithm)*

\[
U_{CNV}(k) = \frac{N(\theta(k)) - P(\theta(k))}{N(\theta(k)) + P(\theta(k))} \cdot G(D(k)) \cdot U_{\text{max}}
\]

➢ The voltage control signal \( U_{CNV} \) will be able to maintain the operating voltage of PV system to its optimum voltage
Another recent issue: Partially Shaded Conditions

(inevitable in PV system practice)

“A condition when some parts of module or array receive less intensity of sunlight”

Causes

- Utility poles
- Trees
- Chimneys or parts of other buildings
- Dirt on the module’s top surface

Under the partially shaded conditions: the shaded cells or modules will force the output current of non-shaded parts to be low following the output current of the shaded ones; Consequently, the output power of PV array is significantly reduced

Significant efforts to solve this kind of mismatching losses

the novel techniques to minimize the losses of partial shading require more additional sensors, auxiliary algorithms and power electronics units
The output characteristic of a photovoltaic (PV) array is changed depending on: solar irradiance, temperature, mismatched cells, array configuration and partially shaded conditions.

Under the Partially Shaded Conditions: The \((I-V)\) and \((P-V)\) characteristics get more complicated with multi-local maximum power point (MPP) (tracking the MPP power is difficult)

Conventional controllers may not guarantee fully working under this condition because they can not distinguish between the global and local peaks since local MPP shows the same typical characteristics as global MPP & they converge to a local MPP.

Thus, the proper amount of power generation can not be utilized by using conventional algorithms when partially shaded occurs.

**MPPT Control must be developed:** To achieve highest possible performance of PV conversion and cover the high cost of solar cells.
APPLICATION FOR PARTIALLY SHADED CONDITIONS

Significant efforts to reduce this kind of mismatching losses:

Shimizu et al. proposed the operation voltage control circuit where dc-dc converter is installed in each module.

Mishima and Ohnishi proposed a system with simplification of output power control of array on a PV string basis.

Kobayashi et al. and Irisawa et al. proposed two sequential stages of MPPT control system.

All the efforts for overcoming the partially shaded problems show that advanced MPPT systems should be developed and the investigation of finding optimal solutions should be increased to get more reliable PV system.
APPLICATION FOR PARTIALLY SHADED CONDITIONS

Modified PV system (PV array; different size & configuration)

PV System

Modified ANN

DC-DC Converter

Fuzzy Logic Controller

E

$E$

$T_c$

$V_{dc}$

$V_{dc}$

$P_{dc}$

$P_{dc}$

$I_{dc}$

$U_{DC}$

$P_{dc} = V_{dc}I_{dc}$
APPLICATION FOR PARTIALLY SHADED CONDITIONS

Siemens SM-55 PV Modules
36 series monocrystalline Si cells

Specification of SM 55 PV module

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum power</td>
<td>55 W</td>
</tr>
<tr>
<td>Open circuit voltage</td>
<td>21.7 V</td>
</tr>
<tr>
<td>Short circuit current</td>
<td>3.45 A</td>
</tr>
<tr>
<td>Voltage at maximum power point</td>
<td>17.4 V</td>
</tr>
<tr>
<td>Current at maximum power point</td>
<td>3.15 A</td>
</tr>
<tr>
<td>STC: AM 1.5, 1000W/m², 25°C</td>
<td></td>
</tr>
</tbody>
</table>

For i=1,2

\[-I_i + I_{ph}(i) - I_s(i) \left[ \exp \left( \frac{q(V_i + I_i R_s(i))}{18n(i)kT(i)} - 1 \right) \right] - \frac{V_i + I_i R_s(i)}{R_p(i)} + I_{sbd} \left[ \exp \left( \frac{q(-V_i)}{n_{bd}kT_{bd}} \right) - 1 \right] = 0\]

\[V_1 + V_2 - V_{load} = 0\]

\[I_1 - I_2 = 0\]

\[q = \text{the electric charge (1.6x10}^{-19}\text{C)}\]
\[k = \text{Boltzmann constant (1.38x10}^{-23}\text{ J/K)}\]

**Bypass diode:** \(I_{sbd}=1.6\times10^{-9}\text{A}, n_{bd}=1.0\) and \(T_{bd}=35^\circ\text{C}\)

Modular Model \(\rightarrow\) PV Array size 3x3 (0.5kW), 20x3 (3.3kW) & PV connection: SP, BL, TCT
APPLICATION FOR PARTIALLY SHADED CONDITIONS

3x3, SP connection

3x3, BL connection

3x3, TCT connection

Area-A

Area-B

Area-C

Area-D

20x3, SP connection

20x3, BL connection

20x3, TCT connection
APPLICATION FOR PARTIALLY SHADED CONDITIONS

Roles of bypass diode:

No shading:
Both bypass diode are in reverse biased voltage
Cell-1 non-shaded,
Cell-2 shaded:
$D_{bd1}$ reverse biased;
$D_{bd2}$ forward biased
Or vice versa

- To prevent the “hot spot problem”
- To give an opportunity to get more power under shading condition

However, The shaded parts can force the optimum voltage to be abnormally low & Multiple peaks

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APPLICATION FOR PARTIALLY SHADED CONDITIONS

PV array size of $A(m,n)$ and the input signals of average irradiance on four adjacent PV modules of $E(r,s)$

For $r = 1: m-1$ and $s=1: n-1$,

$$E(r,s) = 0.25 \times (E_{A(r,s)} + E_{A(r,s+1)} + E_{A(r+1,s)} + E_{A(r+1,s+1)})$$

For 3x3 PV array: 4 input signals of $E$
With dimension 2x2

For 20x3 PV array: 38 input signals of $E$
With dimension 19x2

Modified ANN → input signals for TFFN
APPLICATION FOR PARTIALLY SHADED CONDITIONS

TFFN for 3x3 PV array

\[ E(1,1) = 0.25x(E_{A(1,1)} + E_{A(1,2)} + E_{A(2,1)} + E_{A(2,2)}) \]

\[ E(1,2) = 0.25x(E_{A(1,2)} + E_{A(1,3)} + E_{A(2,2)} + E_{A(2,3)}) \]

\[ E(2,1) = 0.25x(E_{A(2,1)} + E_{A(2,2)} + E_{A(3,1)} + E_{A(3,2)}) \]

\[ E(2,2) = 0.25x(E_{A(2,2)} + E_{A(2,3)} + E_{A(3,2)} + E_{A(3,3)}) \]
APPLICATION FOR PARTIALLY SHADED CONDITIONS

Training Patterns: maximum power point (MPP) voltage ($V_{mp}$) and power ($P_{mp}$) are observed through $P$-$V$ curve for different shading patterns (as shown in the table)

<table>
<thead>
<tr>
<th>Base Irradiance [W/m²]</th>
<th>Pre-determined shading in W/m² on selected modules</th>
</tr>
</thead>
<tbody>
<tr>
<td>200</td>
<td>100</td>
</tr>
<tr>
<td>300</td>
<td>100, 200</td>
</tr>
<tr>
<td>400</td>
<td>100, 200, 300</td>
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<tr>
<td>500</td>
<td>100, 200, 300, 400</td>
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<tr>
<td>600</td>
<td>100, 200, 300, 400, 500</td>
</tr>
<tr>
<td>700</td>
<td>100, 200, 300, 400, 500, 600</td>
</tr>
<tr>
<td>800</td>
<td>100, 200, 300, 400, 500, 600, 700</td>
</tr>
<tr>
<td>900</td>
<td>100, 200, 300, 400, 500, 600, 700, 800</td>
</tr>
<tr>
<td>1000</td>
<td>100, 200, 300, 400, 500, 600, 700, 800, 900</td>
</tr>
</tbody>
</table>

ANN Training Results:

For 3x3 PV array:
SSE = 0.0253
$n_h = 12$

For 20x3 PV array:
SSE = 0.0335
$n_h = 44$

Learning rate = 0.2
Momentum rate = 0.85
# APPLICATION FOR PARTIALLY SHADED CONDITIONS

**ANN Output Verification Performance Index: \( J_v \) and \( J_p \):**

during 12 hours of simulation time

\[
J_v = \int (V_{dc} \cdot V_{mp})^2 dt \\
J_p = \int (P_{dc} \cdot P_{mp})^2 dt
\]

<table>
<thead>
<tr>
<th>Irradiance</th>
<th>PV array</th>
<th>non-shaded</th>
<th>25%-shaded</th>
<th>50%-shaded</th>
<th>75%-shaded</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slow changes</td>
<td></td>
<td>( J_v )</td>
<td>( J_p )</td>
<td>( J_v )</td>
<td>( J_p )</td>
</tr>
<tr>
<td>3x3</td>
<td>SP</td>
<td>0.247</td>
<td>5.975</td>
<td>0.509</td>
<td>16.303</td>
</tr>
<tr>
<td></td>
<td>BL</td>
<td>0.247</td>
<td>5.975</td>
<td>0.266</td>
<td>19.533</td>
</tr>
<tr>
<td></td>
<td>TCT</td>
<td>0.247</td>
<td>5.975</td>
<td>0.269</td>
<td>5.757</td>
</tr>
<tr>
<td>Rapid changes</td>
<td></td>
<td>( J_v )</td>
<td>( J_p )</td>
<td>( J_v )</td>
<td>( J_p )</td>
</tr>
<tr>
<td>3x3</td>
<td>SP</td>
<td>1.029</td>
<td>5.295</td>
<td>4.158</td>
<td>14.945</td>
</tr>
<tr>
<td></td>
<td>TCT</td>
<td>1.029</td>
<td>5.295</td>
<td>1.250</td>
<td>6.280</td>
</tr>
<tr>
<td>Slow changes</td>
<td></td>
<td>( J_v )</td>
<td>( J_p )</td>
<td>( J_v )</td>
<td>( J_p )</td>
</tr>
<tr>
<td>20x3</td>
<td>SP</td>
<td>0.338</td>
<td>7.853</td>
<td>0.618</td>
<td>15.306</td>
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<td></td>
<td>BL</td>
<td>0.338</td>
<td>7.853</td>
<td>0.457</td>
<td>20.654</td>
</tr>
<tr>
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<td>0.338</td>
<td>7.853</td>
<td>0.358</td>
<td>9.798</td>
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<tr>
<td>Rapid changes</td>
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<td>( J_v )</td>
<td>( J_p )</td>
<td>( J_v )</td>
<td>( J_p )</td>
</tr>
<tr>
<td>20x3</td>
<td>SP</td>
<td>1.463</td>
<td>8.014</td>
<td>5.378</td>
<td>16.403</td>
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<tr>
<td></td>
<td>TCT</td>
<td>1.463</td>
<td>8.014</td>
<td>2.253</td>
<td>10.935</td>
</tr>
</tbody>
</table>
DEVELOPMENT OF REAL-TIME SIMULATOR

Main reasons of using real-time simulator:
“Various possible input scenarios”→ very difficult to examine the behavior of proposed system in the real-system

Advantages:
• To overcome field testing (costly & time consuming)
• “What-if scenarios” can be simply simulated
• To allow increasing experience of the PV system behavior as well as in actual system

Light intensity is Measured in Lux
(1 Lux = 0.0161028 W/m²)

Virtual PV system with MPPT controller

Time accelerated mode:
1 sec in simulation = 1 hour in real practice
Real-time simulation results in different input scenarios on PV modules

Irradiance level from 300W/m² to 800W/m² for SM-55 type PV module

“The results confirm that the proposed technique is robust and insensitive to changes in these weather conditions”
SIMULATION RESULTS

**Slow changes in irradiance**
‘clear sky measurement’
(6am-6pm)

**Quick changes in irradiance**
‘cloudy sky measurement’
(6am-6pm)
DC voltage, control signal DC power for SM-55 PV module

SIMULATION RESULTS

- DC Voltage (V)
- DC Power (W)
- Control Signal, $U_{CNV}$ (V)

Graphs showing the simulation results over time (hours) with variations in irradiance level and cell temperature.
The accuracy between the dc voltage controller output ($V_{dc}$) and the optimum voltage from the ANN ($V_{dc^*}$) is measured by ARE & RE

**Average relative error (ARE):**

$$ARE = \frac{1}{K} \sum_{i} \left| \frac{V_{dc} - V_{dc^*}}{V_{dc^*}} \right| \times 100 \%$$

**Relative error (RE) to the estimated optimum voltage:**

$$RE = \frac{\sum_{i} V_{dc^*} \Delta t}{\sum_{i} V_{dc} \Delta t} \times 100 \%$$

<table>
<thead>
<tr>
<th>Irradiance</th>
<th>SM-55</th>
<th></th>
<th>FS-50</th>
<th></th>
<th>US-21</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ARE(%)</td>
<td>RE(%)</td>
<td>ARE(%)</td>
<td>RE(%)</td>
<td>ARE(%)</td>
<td>RE(%)</td>
</tr>
<tr>
<td>Step change</td>
<td>0.167</td>
<td>0.115</td>
<td>0.895</td>
<td>0.542</td>
<td>0.410</td>
<td>0.121</td>
</tr>
<tr>
<td>Slow shading</td>
<td>0.251</td>
<td>0.165</td>
<td>0.966</td>
<td>0.678</td>
<td>0.590</td>
<td>0.194</td>
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<tr>
<td>Quick shading</td>
<td>0.327</td>
<td>0.127</td>
<td>1.283</td>
<td>0.735</td>
<td>0.733</td>
<td>0.212</td>
</tr>
<tr>
<td>Slow changes</td>
<td>1.651</td>
<td>0.753</td>
<td>2.845</td>
<td>0.947</td>
<td>2.054</td>
<td>0.816</td>
</tr>
<tr>
<td>Rapid changes</td>
<td>1.837</td>
<td>0.925</td>
<td>3.086</td>
<td>1.134</td>
<td>2.135</td>
<td>0.962</td>
</tr>
</tbody>
</table>
SIMULATION RESULTS

Comparison of Control Performance with the Proportional-Integral (PI) controller

Proportional gain \((K_p) = 1.5\)
Integral gain \((K_i) = 0.75\)

The reason for comparing our proposed controller: to show the robustness, stability and accuracy over the conventional PI controller

Performance index of both controllers during 12 hours of simulation time

\[ J = \int (V_{dc} \ast -V_{dc})^2 \, dt \]

<table>
<thead>
<tr>
<th></th>
<th></th>
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<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Step change</td>
<td>0.0666</td>
<td>0.0109</td>
<td>5.278</td>
<td>2.587</td>
<td>0.7102</td>
<td>0.1205</td>
</tr>
<tr>
<td>Slow shading</td>
<td>0.2207</td>
<td>0.0498</td>
<td>6.678</td>
<td>3.384</td>
<td>0.5897</td>
<td>0.0942</td>
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<tr>
<td>Quick shading</td>
<td>0.2268</td>
<td>0.1067</td>
<td>8.997</td>
<td>4.605</td>
<td>0.7331</td>
<td>0.2121</td>
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<tr>
<td>Slow changes</td>
<td>3.7040</td>
<td>1.0880</td>
<td>14.812</td>
<td>5.932</td>
<td>5.0630</td>
<td>0.7665</td>
</tr>
<tr>
<td>Rapid changes</td>
<td>3.9245</td>
<td>1.1750</td>
<td>15.735</td>
<td>6.237</td>
<td>5.1234</td>
<td>0.7883</td>
</tr>
</tbody>
</table>
Step changes in Irradiance & cell temperature

SM-55 PV module voltage and current

FS-50 PV module voltage and current

Other results → RBF methods:

Daily condition of irradiance & cell temp.


FIGURE 20. PV modules voltage for the third scenario (‘-’ ideal MPP voltage, ‘.’ the proposed method, ‘- -’ open circuit voltage method, ‘.’ P&O method).
SIMULATION RESULTS

Real-time simulation results under partially shaded conditions

Shading patterns of irradiance level

![Irradiance Graphs](image)

a. Slow changes in irradiance
b. Rapid changes in irradiance
SIMULATION RESULTS

3x3, SP connection

DC Voltage (V)

Vdc
Vdc*
Vdc_75%
Vdc*_75%
Vdc_50%
Vdc*_50%
Vdc_25%
Vdc*_25%

DC Power (W)
Pdc
Pdc*
Pdc_75%
Pdc*_75%
Pdc_50%
Pdc*_50%
Pdc_25%
Pdc*_25%

Control Signal, U

non-shaded
75%-shaded
50%-shaded
25%-shaded
The control responses are verified through an performance index during 12 hours of simulation time

\[ J = \int (V_{dc} \times -V_{dc})^2 dt \]

For 3x3 PV array:

<table>
<thead>
<tr>
<th>Irradiance</th>
<th>PV array</th>
<th>non-shaded</th>
<th>25%-shaded</th>
<th>50%-shaded</th>
<th>75%-shaded</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slow changes</td>
<td>SP</td>
<td>0.493</td>
<td>1.131</td>
<td>2.406</td>
<td>16.501</td>
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<tr>
<td></td>
<td>BL</td>
<td>0.493</td>
<td>0.592</td>
<td>0.948</td>
<td>1.729</td>
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<tr>
<td></td>
<td>TCT</td>
<td>0.493</td>
<td>0.597</td>
<td>0.798</td>
<td>0.814</td>
</tr>
<tr>
<td>Rapid changes</td>
<td>SP</td>
<td>2.057</td>
<td>9.239</td>
<td>13.846</td>
<td>20.178</td>
</tr>
<tr>
<td></td>
<td>BL</td>
<td>2.057</td>
<td>5.462</td>
<td>10.655</td>
<td>13.337</td>
</tr>
<tr>
<td></td>
<td>TCT</td>
<td>2.057</td>
<td>2.778</td>
<td>7.216</td>
<td>4.893</td>
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</tbody>
</table>
**SIMULATION RESULTS**

$V_{dc}$ and $P_{dc}$ outputs of 20x3 array configuration under partially shaded conditions

Assumed: The initial point for P&O is the voltage close to $V_{oc}$

<table>
<thead>
<tr>
<th>time (h)</th>
<th>Shading patterns on modules area (W/m²)</th>
<th>SP</th>
<th>Proposed Controller</th>
<th>BL</th>
<th>Proposed Controller</th>
<th>TCT</th>
<th>Proposed Controller</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>P &amp; O</td>
<td>$V_c (V)$</td>
<td>$P_d (W)$</td>
<td>$V_{oc} (V)$</td>
<td>$P_{oc} (W)$</td>
<td>$V_c (V)$</td>
</tr>
<tr>
<td>10.00</td>
<td>250 150 250 750</td>
<td>P &amp; O</td>
<td>320.60</td>
<td>485.66</td>
<td>223.32</td>
<td>546.33</td>
<td>320.60</td>
</tr>
<tr>
<td>10.30</td>
<td>150 500 750 750</td>
<td>P &amp; O</td>
<td>340.50</td>
<td>514.65</td>
<td>236.58</td>
<td>1179.40</td>
<td>340.50</td>
</tr>
<tr>
<td>11.00</td>
<td>500 750 1000 1000</td>
<td>P &amp; O</td>
<td>333.87</td>
<td>1683.30</td>
<td>234.37</td>
<td>1747.30</td>
<td>333.87</td>
</tr>
<tr>
<td>11.30</td>
<td>250 500 750 1000</td>
<td>P &amp; O</td>
<td>338.29</td>
<td>854.30</td>
<td>238.79</td>
<td>1199.80</td>
<td>338.29</td>
</tr>
<tr>
<td>12.00</td>
<td>500 250 500 750</td>
<td>P &amp; O</td>
<td>331.66</td>
<td>835.98</td>
<td>223.32</td>
<td>1559.00</td>
<td>331.66</td>
</tr>
<tr>
<td>12.30</td>
<td>150 500 150 500</td>
<td>P &amp; O</td>
<td>313.97</td>
<td>465.73</td>
<td>139.30</td>
<td>663.79</td>
<td>313.97</td>
</tr>
<tr>
<td>1.00</td>
<td>500 750 150 250</td>
<td>P &amp; O</td>
<td>329.45</td>
<td>499.30</td>
<td>150.35</td>
<td>737.26</td>
<td>329.45</td>
</tr>
<tr>
<td>1.30</td>
<td>750 500 250 500</td>
<td>P &amp; O</td>
<td>331.66</td>
<td>835.98</td>
<td>223.32</td>
<td>1559.00</td>
<td>331.66</td>
</tr>
<tr>
<td>2.00</td>
<td>1000 750 500 250</td>
<td>P &amp; O</td>
<td>338.29</td>
<td>854.30</td>
<td>238.79</td>
<td>1199.80</td>
<td>338.29</td>
</tr>
<tr>
<td>2.30</td>
<td>1000 1000 750 500</td>
<td>P &amp; O</td>
<td>333.87</td>
<td>1683.30</td>
<td>234.37</td>
<td>1747.30</td>
<td>333.87</td>
</tr>
<tr>
<td>3.00</td>
<td>750 750 150 150</td>
<td>P &amp; O</td>
<td>320.60</td>
<td>476.33</td>
<td>143.72</td>
<td>1014.80</td>
<td>320.60</td>
</tr>
</tbody>
</table>
**CONCLUSION**

ANN-fuzzy logic with polar information based MPPT control

**Testing**

A. Under Uniform Insolation Condition

- Different PV modules technologies:
  - Siemens SM-55 (c-Si)
  - First Solar FS-50 (Thin-film CdTe)
  - USSC US-21 (3j a-Si)

B. Under Partially Shaded Condition (SM-55)

- Different PV array configurations:
  - Series-Parallel (SP)
  - Bridge Link (BL)
  - Total Cross Tied (TCT)

- Different PV array size:
  - 3x3 (0.5kW)
  - 20x3 (3.3kW)

**Verification**

- Developed real-time simulator based dSPACE real-time interface system

**Overall results:**

- Robust & insensitive to fast & slow variations in irradiance & temperature
- It achieves to enhance the dynamic behavior of the MPPT controller without retuning the gain parameters
Performance of TFFN, RBF and ANFIS networks for different technology of PV modules


Motivation-2

- Markets of non-crystalline silicon cells
- Concentration on c-Si solar cell technology
- Different MPP points characteristic
- Efficiency

ANN structures: RBF, ANFIS, TFFN
Introduction

- Investigation on three different ANN structures for identification the optimum operating voltage of non c-Si PV modules
- Type of PV modules: double junction amorphous Si (2j a-Si), triple junction amorphous Si (3j a-Si), Cadmium Indium Diselenide (CIS) and thin film Cadmium Telluride (CdTe) solar cell technologies
- Indicators for ANN models: the flexibility of training process, the simplicity of network structure and the accuracy of validation error
Description of the model
(Modeling of PV modules)

- Expansion for non c-Si solar cells due to the development of nano-material technology
- The main reason of this trend is to cut the manufacturing cost of conventional Si PV modules

Other properties:
- much cheaper for the same efficiency conversion, especially under massive production of cells
- low cost
- light weight
- flexible
- more versatile with very small amount of Silicon needed
- energy payback is very fast
  (2 months, compared with 4 years for conventional Si technology)

“In the end, the non c-Si solar cell technologies are potential to be inexpensive to produce and they could dominate the world production in the future”
Description of the model
(Modeling of PV modules)

PV module types:
- Solarex MST-43MV (2j a-Si)
- USSC UniSolar US-32 (3j a-Si)
- Siemens ST-40 (CIS)
- First Solar FS-50 (thin film CdTe)

Specifications under 1000W/m² and 25°C

<table>
<thead>
<tr>
<th>PV modules</th>
<th>$I_{SC}$ (A)</th>
<th>$V_{OC}$ (V)</th>
<th>$I_{MPP}$ (A)</th>
<th>$V_{MPP}$ (V)</th>
<th>$P_{MPP}$ (W)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MST-43MV</td>
<td>0.787</td>
<td>101.0</td>
<td>0.616</td>
<td>71</td>
<td>43.74</td>
</tr>
<tr>
<td>US-32</td>
<td>2.4</td>
<td>23.8</td>
<td>1.94</td>
<td>16.5</td>
<td>32.01</td>
</tr>
<tr>
<td>ST-40</td>
<td>2.59</td>
<td>22.2</td>
<td>2.41</td>
<td>16.6</td>
<td>40.00</td>
</tr>
<tr>
<td>FS-50</td>
<td>1.0</td>
<td>90</td>
<td>0.77</td>
<td>65</td>
<td>50.05</td>
</tr>
</tbody>
</table>

Solarex MST-43MV, USSC UniSolar US-32
(tandem junction and triple junction thin-film module amorphous silicon cells)
“Effectively using the conversion of sunlight”
- The bottom cell (red light), the middle cell (green light) and the top cell (blue light)
- The major development: efficiency and stability
- Optimum conversion of different segments of the spectrum

Siemens ST-40
(Cadmium Indium Diselenide (CIS) solar cells).
✓ characterized by exceptional spectral response and long-term performance integrity
✓ Efficiency is almost similar to crystalline photovoltaic modules

First Solar FS-50
(CdTe based thin-films technology)
- Recommended for high output voltage
- Very thin layers of compound semiconductor material with low temperature coefficients which provides for cost effective and greater energy production
The characteristics of \( I_{sc} \) and \( V_{oc} \) are almost similar for all semiconductor types of solar cells.

However, there might be different characteristics at \( V_{MPP} \).

The correlation \( V_{MPP} = f(E, T_c) \) is non-linear.

“In this respect, to operate the PV modules at their maximum power point, tracking the optimum voltage using intelligent technique by means a functional reasoning method for function approximation is totally necessary.”
**ANN structures based optimum voltage**

**Radial Basis Function (RBF):**
- Strong network
- Fast training process
- Direct confirmation of structure
- *But, end up with complicated structure, in case of complex data*

**Algorithm:**
- Local mapping, instead of global mapping as in MLP structure
- In MLP; all inputs cause output; RBF; only input near the receptive fields produce the activation function (hidden layer)

The radial basis output layer $a_1$: the Euclidean distance weight function ‘dist’ is applied between the input signals, $[E; T_c]$ and weights, $w_1$ before preceding them to the ‘radbas’ transfer function

$$a_1(n) = \text{radbas}[\text{dist}(w_1(n,1)E + w_1(n,2)T_c)b_1(n,1))]$$

The output layer $a_2$: by simply applying the “purelin” transfer function between $a_1$ outputs and weights $w_2$, include the bias $b_2$ of the second layer

$$a_2(m) = \text{purelin}[(\sum_{n=1}^{n}w_2(m,n)x_a1(n)) + b_2(1,1)]$$
ANN structures based optimum voltage)

Adaptive Neuro-Fuzzy Inference System (ANFIS)
• Especially designed for single output, called Sugeno type fuzzy inference system
• Hybrid learning algorithm (combine the least square and back propagation gradient descent methods for training the mf parameters)
• Fast training process & high accuracy
• But, for multi-objective optimization → multi anfis network and must be individually trained.
ANFIS network structures (cont.)

Layer-1: Grade of mf

\[ O_1 = \mu_{A_i}(x) \]

Layer-2: Firing strength

\[ O_2 = w_i = \prod_{j=1}^{m} \mu_{A_i}(x) \]

Layer-3: Normalization of firing strength

\[ O_3 = \frac{w_i}{w_1 + w_2} \]

Layer-4: Rule outputs

\[ O_4 = y_1 = w_1(p_i x_1 + q_i x_2 + r_i) \]

\[ O_5 = \sum_i y_i = \sum_i w_1(p_i x_1 + q_i x_2 + r_i) + \sum_i w_2(p_2 x_1 + q_2 x_2 + r_2) + \ldots \]

p, q, r are the coefficient parameters of the \( n \)th rule through the first order polynomial form expressed in the first order Sugeno fuzzy model.
In the hidden and output layers, the sigmoid function is utilized for the input-output characteristics of the nodes. For each node $i$, the output $O_i(k)$ is given by:

$$O_i(k) = \frac{1}{1 + e^{-I_i(k)}}$$

where $I_i(k)$ is the input signal to node $i$ at the $k$-th sampling and this is given by the weighted sum of the input nodes:

$$I_i(k) = \sum_j w_{ij}(k)O_j(k)$$

and $w_{ij}$ is the connection weight from node $j$ to node $i$. $O_j(k)$ is the output from node $j$.

During the training, the connection weights $w_{ij}$ are tuned recursively until the best fit is achieved for the input–output patterns based on the minimum value of the sum of the squared errors (SSE):

$$SSE = \sum_{k=1}^{N} (t(k) - O(k))^2$$

where $N$ is the total number of training patterns, $t(k)$ and $O(k)$ are the $k$-th output target and estimated values of MPPs voltage-power.

During the training process:
- learning rate = 0.2
- momentum rate = 0.85
SIMULATION RESULTS

Data Set for Training Process

- To set the functions between input and output through the hidden layers (training data set should be selected to cover the entire region where the network is expected to operate)
- Training data pattern \( \rightarrow [V_{\text{mpp}}] = f(E, T_c) \); following the mathematical model of SNL
- Total data (228 sets) for operating conditions between 15-65°C and 100-1000W/m²

Input signals for validation

a. Ramp signal; 
\[ E = 90t + 100 \text{ (W/m²)} \] and \( T_c = 5.5t + 10 \text{ (°C)} \); for \( 0 < t < 10 \text{sec} \)
b. Random signal; where the mean of \( E \) and \( T_c \) are 800W/m² and 50°C, respectively, with variance=1.0
c. Repeating sequence; 
\[ E = 450t + 100 \text{ (W/m²)} \] and \( T_c = 27.5t + 15 \text{ (°C)} \);
for the periodic time \( 0 < t < 2 \text{sec} \) within 10sec of time simulation
d. Uniform random number; \([E_{\text{min}}=100 \text{W/m²} - E_{\text{max}}=1000 \text{W/m²}] \) and \([T_{c\text{min}}=10 \text{°C} - T_{c\text{max}}=65 \text{°C}] \)

Results for Training Process

<table>
<thead>
<tr>
<th>PV modules</th>
<th>RBF</th>
<th>ANFIS</th>
<th>TFFN</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( n_h )</td>
<td>SSE</td>
<td>( n_h )</td>
</tr>
<tr>
<td>MST-43MV</td>
<td>12</td>
<td>0.000375</td>
<td>21</td>
</tr>
<tr>
<td>US-32</td>
<td>4</td>
<td>0.000608</td>
<td>21</td>
</tr>
<tr>
<td>ST-40</td>
<td>5</td>
<td>0.000948</td>
<td>21</td>
</tr>
<tr>
<td>FS-50</td>
<td>11</td>
<td>0.000739</td>
<td>21</td>
</tr>
</tbody>
</table>

**Performance index**

\[
J = \sqrt{\frac{\sum_{i=1}^{N} (V_{\text{op}}^i - V_{\text{MPP}}^i)^2}{\sum_{i}^{N} (V_{\text{MPP}}^i - \bar{V}_{\text{MPP}})^2}}
\]

\( N \) is the number of parameter data set, \( i \) is the \( i^{th} \) sample of data, \( V_{\text{MPP}} \) is the ideal voltage at maximum power point, \( V_{\text{op}} \) is the estimated optimum voltage and
Typical results with random input signals

- **Solarex MST-43MV (2j a-Si)** with RBF network
- **USSC Unisolar US-32 (3j a-Si)** with ANFIS network
- **Siemens ST-40 (CIS)** with TFFN network
- **First Solar FS-50 (thin film CdTe)** with RBF network
## SIMULATION RESULTS (cont.)

### Performance index during validation process

<table>
<thead>
<tr>
<th>PV modules</th>
<th>ramp signal</th>
<th>random signal</th>
<th>repeating sequence signal</th>
<th>uniform random signal</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RBF</td>
<td>ANFIS</td>
<td>TFFN</td>
<td>RBF</td>
</tr>
<tr>
<td>MST-43MV</td>
<td>0.035</td>
<td>0.096</td>
<td>0.065</td>
<td>0.258</td>
</tr>
<tr>
<td>US-32</td>
<td>0.143</td>
<td>0.007</td>
<td>0.059</td>
<td>2.474</td>
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<tr>
<td>ST-40</td>
<td>0.221</td>
<td>0.146</td>
<td>0.143</td>
<td>1.912</td>
</tr>
<tr>
<td>FS-50</td>
<td>0.063</td>
<td>0.115</td>
<td>0.081</td>
<td>0.205</td>
</tr>
</tbody>
</table>

### Evaluation performance of ANN Models

<table>
<thead>
<tr>
<th>ANN models</th>
<th>Flexibility</th>
<th>Simplicity of network structure</th>
<th>Accuracy of validation error</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Training process</td>
<td></td>
<td>MST-43MV</td>
</tr>
<tr>
<td>RBF</td>
<td>high</td>
<td>moderate</td>
<td>high</td>
</tr>
<tr>
<td>ANFIS</td>
<td>high</td>
<td>low</td>
<td>low</td>
</tr>
<tr>
<td>TFFN</td>
<td>moderate</td>
<td>high</td>
<td>moderate</td>
</tr>
</tbody>
</table>
Conclusion

Different models of artificial neural network to deal with the $V_{MPP}$ of non crystalline Si PV modules

The trained configurations are verified using ramp, random, repeating sequence and uniform random signals of irradiance and cell temperature

The simulation results confirm that RBF and ANFIS methods have the flexible training process; while the TFFN method has simpler network structure than others

For the accuracy of validation error, RBF and ANFIS models are more suitable for 2j a-Si and 3j a-Si PV models, respectively. On the other hand, ANFIS and TFFN are effectively used in CIS technology. For thin film CdTe technology, the RBF and TFFN methods are the best option